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EXPERIMENTAL ANALYSIS OF STRESS UNDER DIFFERENT CONDITIONS USING ELECTROGRAPH AND ELECTRODERMAL ACTIVITY

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ABSTRACT

When people face obstacles, expectations, or circumstances that they view as dangerous, overpowering, or beyond their capacity to handle, they feel stress, a physiological and psychological reaction. In this publication, we have collected signals from a variety of participants using both Electrocardiography (ECG) and Electrodermal Activity (EDA). Each person has two electrodes put on their fingertips to capture signals in the BIOPAC MP36 system under three different conditions: stress, deep breathing technique (DBT), and repose. Following the acquisition of all data in the BIOPAC system, the signals are sent to the KUBIOS program, which uses them to extract significant HRV (Heart Rate Variability) properties. The KUBIOS program extracts 38 characteristics in total, and several graphs are created for stress analysis based on these data. These graphs give us a clear idea about variation in different HRV parameters wherein subject is under supine, DBT and stressed conditions. Through the analytical study, we observed that stress index is higher when subjects are put under stressed state while as, stress index came out to be lower during DBT state. This clearly shows that EDA signals are effectively analyzing variations in different HRV parameters and is able to recognize stress in healthy subjects.

KEYWORDS: HRV (Heart Rate Variability), KUBIOS Software, Deep Breathing Technique (DBT)

1. INTRODUCTION

Stress is one of the most pervasive and multi-faceted aspects of modern life. Stress is a complex combination of physiological and psychological reactions that occur when faced with a variety of challenges or demands. Stress is a dynamic process that affects not only the mind, but also the body [1,2]. Stress is a reflection of the complex mechanisms and adaptations that the human body has developed to cope with the stresses and uncertainties of today's world. Stress is not just a mental state, but a holistic response that includes hormonal changes, activation of the autonomic nervous system, cognitive alterations, and emotional responses. [3].

However, when considering the effectiveness of physiological signals for stress analysis, ECG and EDA stand out as particularly valuable modalities. ECG, or Electrocardiography, offers insights into the heart's electrical activity and heart rate variability (HRV), making it a reliable indicator of autonomic nervous system (ANS) activity[4]. ECG provides data over longer time frames, making it suitable for detecting chronic stress patterns and gradual changes in HRV parameters[5]. On the other hand, EDA, or Electrodermal Activity, is highly sensitive to emotional arousal and acute stress responses [6, 7]. It excels in capturing immediate, real-time stress reactions, allowing for the rapid detection of acute stressors. EDA signals are also less susceptible to motion artifacts, making them ideal for ambulatory monitoring and real-world stress assessments.

2. METHODOLOGY

The main objectives that will be covered in this research are mentioned below:

- To acquire data and collect recordings of ECG/ EDA using BIOPAC MP36 system of various healthy subjects.
- To extract various HRV features from given ECG signals on KUBIOS Software
- To analyze and identify stressed and non-stressed patients based on ECG signals

In order to depict how stress can be identified and analyzed using ECG signals, we have performed a few steps that are shown in Figure 1. Moreover, the detailed description of each step is explained in this section.

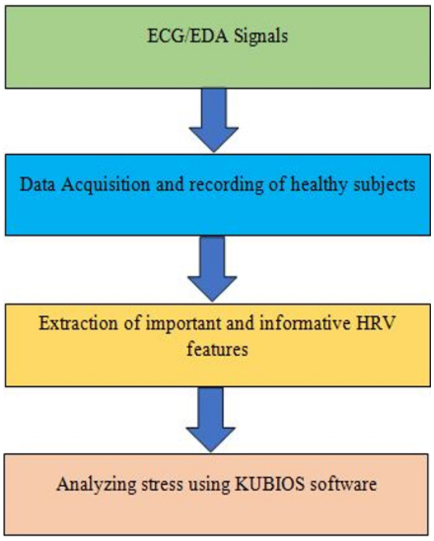

Fig. 1. Flowchart of proposed work

The signals acquired for ECG and EDA by following above mentioned process is displayed on the computer screen. Figure 2 demonstrates the sample of signals acquired for individuals. It must be noted here, that same process is followed when the subject is put under stressed condition with arithmetic problems and then DBT state.

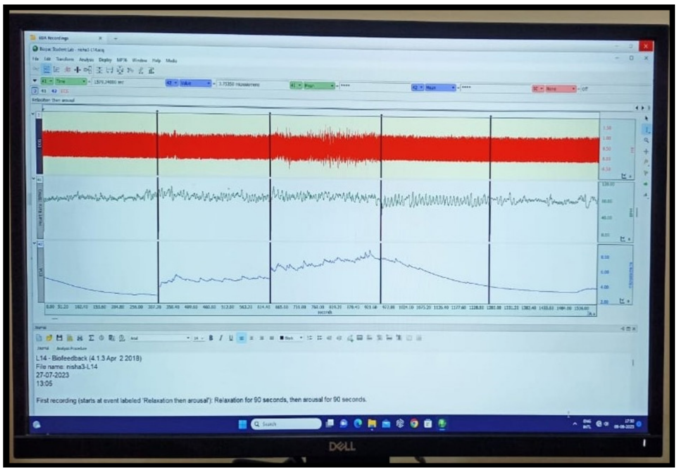

Fig 2. Signals of the sample

2.1 Extracting HRV

Now that you have all the information you need, it's time to get the HRV features out of the given signals. This step is a mix of several tasks. KUBIOS software will be used for HRV analysis, and tachogram will be used to define the sampling rate. During this phase, the data (as signals) will be imported into the software. Then, tachograms will be created for the HRV analysis. The data obtained from different subjects in.xls format will be passed into KUBIOS using the import feature for the analysis of the variation of various features under three conditions: First, Tachograms are created. The window length is set to 5 minutes between 2 RR intervals. Tachograms help human system to deal with the stress and uncertainty of today's world. It's not just a mental state. It's a holistic response, including hormonal fluctuations, Autonomic Nervous System Activation, Cognitive Changes, and Emotional reactions, among others.. This is immediately followed up by the HRV analysis wherein a total of 38 HRV features from the given RR intervals are extracted. Below given Figure 3 shows HRV results of a subject attained in KUBIOS software

In the last step of proposed work, analytical study is performed wherein the impact of various features or attributes is observed for stress identification. KUBIOS provides various tools for visualizing HRV results, including graphs and charts that display HRV parameter values and trends. Here, we have calculated the mean and median value of all 38 features for supine, DBT and stress conditions for analyzing the variations. The results obtained are analyzed and explained in the next part of this paper.

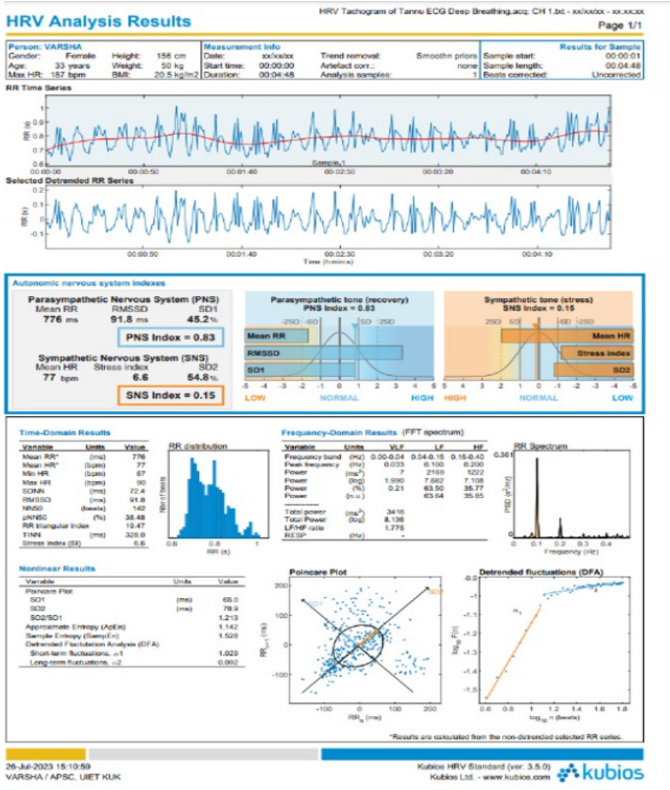

Fig. 3. HRV analysis of Subject 2.

3. RESULTS & FINDINGS

The analytical study of our work is conducted in KUBIOS software wherein the graphs are obtained for three different conditions i.e., Supine, DBT and stress for analyzing variations in ECG signals. As mentioned earlier, we have extracted 38 HRV features from the signals, therefore, in this part we will be observing the variations shown by different features while changing position from one state to another.

3.1 Analysis for Supine:

We have first analyzed the variations of ECG signals for supine state, wherein the students are lied down comfortably in relaxing position and signals are recorded through two electrodes placed at their fingers. The mean variations of the supine are shown in Figure 4, with x-axis denoting different features and y-axis denoting their mean values respectively. While studying the graph, it is clear that in supine condition the features LF (ms^2), HF (ms^2) and total power (ms^2) are showcasing high values of 1500, 1292 and 2917 in Figure while as, the value of other HRV parameters is significantly far below than 500. However, the mean value of stress index in this case is only 8.88, which is considerably low. This signifies that even when the subject is in supine position the stress can still be detected.

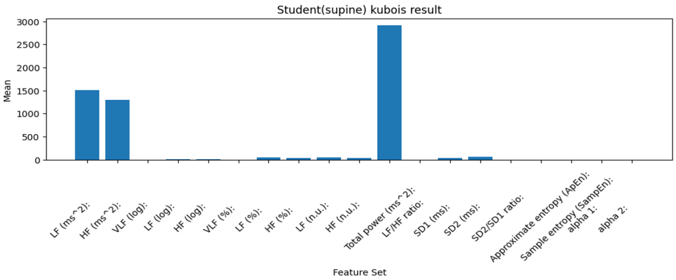

Fig. 4. Mean graphs for supine state

3.2 Analysis under DBT

Just like supine state, we are going to analyze the variations in features when healthy subjects were put on DBT state. During this DBT state the subjects undergo through deep inhaling and exhaling process causing variations in various features respectively. The mean of the various HRV features during DBT state is demonstrated in Figure 5. The x and y graphs of the graph calibrate to the different HRV features and their respective mean score respectively. After carefully reviewing the graph, we observed that value of mean RR and total power are showcasing exceptionally high mean scores of 700 and 7000 respectively. On the other hand, the mean value of TINN parameter is 400 and 6300 in LF parameters. Nonetheless, the mean value of stress index in DBT state is only 6.45 which is far lower than what we saw in supine state.

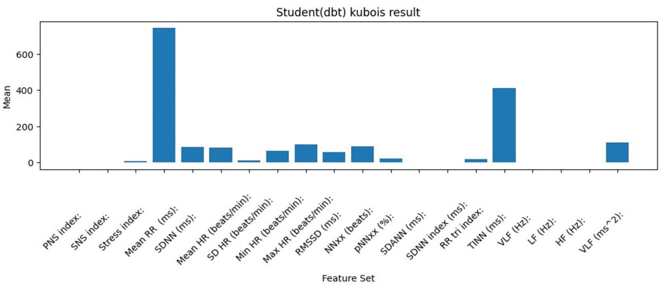

Fig. 5. Mean graph for DBT state

3.3 Analysis under Stress

In the last category of our work, we have analyzed the variation in various HRV parameters when subject is put under stressed condition. To create that stress in subjects, we have given them some arithmetic question for solving. The mean or average value of features attained in this case is shown in Figure 6, wherein x and y-axis depict different HRV parameters and their respective mean values during stressed conditions. The graphs reveal that level of total power parameter is increasingly high near 1750, whereas, it was near to 1100 and 470 for LF and HF parameters respectively. Also, the stress index in this state is going up with a mean value of 10.28, signifying the subject is in stressed state.

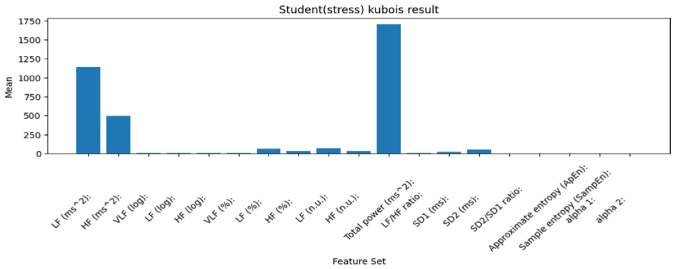

Fig. 6. Mean graph for Stress state

5. CONCLUSION

In proposed analysis of ECG and EDA signals using KUBIOS software across three distinct conditions—Supine, DBT (Deep Breathing Technique), and stress—we sought to explore how specific HRV parameters could aid in identifying stress levels in individuals. Throughout the investigation, elevated values for HRV parameters, such as Mean RR, Total Power, LF (Low Frequency), HF (High Frequency), and TINN (Triangular Interpolation of RR intervals), across the three conditions are observed. In the Supine condition, where subjects are in a relaxed and non-stressed state, it is found that HRV parameters exhibited mean values within the range of 800 to 1200. Conversely, during the Deep Breathing Technique (DBT) condition, where subjects engaged in controlled inhaling and exhaling exercises, we observed a distinctive pattern. Mean RR and TINN displayed mean scores close to 700, signifying the rhythmic nature of deep breathing. In the stress condition, when subjects were subjected to stressors, HRV parameters exhibited elevated mean values for stress index with 10.28 indicating heightened stress levels.

These findings underscore the potential of HRV parameters extracted from EDA signals as reliable and sensitive markers of stress across varying conditions. Such insights hold significant promise for enhancing stress assessment and facilitating more effective stress management strategies in both research and clinical contexts.

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